Group- and individual-level successes in human-agent teams: From trade-off to win-win

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Abstract
When it comes to the success of a team, every individual player counts. The present position paper addresses four propositions to envision how our future partnerships with intelligent agents can introduce more opportunities for individual team members to shine in their unique ways. Specifically, we elaborate on relevant design principles (e.g., human-centered design, implicit interaction, and unremarkable computing) and discuss potential applications of artificial intelligence (AI) in future human-agent teamwork. Instead of focusing on short-term performance outcomes, we posit future human-machine teamwork should pay more attention to resolving common challenges in human-human teams, dedicating to creating a more supportive and inclusive work environment.

Author Keywords
human-agent teamwork, human-machine partnership, autonomous agent, teamwork, collaboration

CCS Concepts
•Human-centered computing $\rightarrow$ Collaborative and social computing theory, concepts and paradigms; Human computer interaction (HCI);

Introduction

Team successes arise when individual members can play the best version of themselves. In today's fast-pacing work environment, this is often overlooked, prioritizing the group's interests over individuals'. As a result, we may see a team flourishes in the short term, while the bonds among teammates are gradually falling apart. Moreover, the tendency to sacrifice individuals' interests can reinforce vulnerability of marginalized teammates. While we vision the future of human-machine partnerships, how do we mitigate instead of exacerbating these universal team challenges? In the present position paper, we draw from interdisciplinary perspectives and propose four propositions to address the balance between group- and individual-level team successes.

Proposition 1: Humans at the center of human-agent teamwork

Ever since researchers first explored human-machine teamwork, there have been continuous debates over whether machines should work *with* or work *for* human teammates [3, 22]. In our view, the question should be addressed through two parallel approaches. The first concerns the context of a teamwork task. For instance, how we can take advantage of an AI-mediated writing tool differs substantially while we are composing a financial report versus science fiction. Second, to practice a human-centered perspective for the future human-agent collaborative framework, we should offer opportunities for users not only to articulate their needs and goals but also to position their strengths in a team. To implement these ideals in building autonomous agents, we see the usefulness of including customizable features allowing users to input pre-defined rules to guide their machine teammates. This also implies algorithmic models that drive future agents should not focus on team outcomes as a sole dimension for optimization (as shown in a recent review [17], team performance remains the primary measurement in human-robot teams), but user-defined metrics should also be taken into account.

Proposition 2: Implicit design for individual accommodations

Well before the recent advances in machine learning, scholars have proposed the ideas of "unremarkable computing" [20, 23], suggesting that even with the aim to generate behavioral changes, technology should intervene in a subtle and mellow fashion, minimizing users' discomfort and avoidance. Similarly, while we look to future autonomous agents to set the ground for individual teammates to shine, it is also important that they do so in a comfortable way without awkwardly putting users "on the spot". In this regard, we first see the need to further explore individual differences in their responses (e.g., openness, interest) to interacting with computer-mediated agents. For instance, recent reviews suggest that individuals' acceptance of robots are often subject to their personality traits [1, 2]. Through understanding individuality, we can better identify to whom and how autonomous agents can offer effective aids in human-machine partnerships. For example, by alleviating the stress of peer judgments, socially anxious individuals may particularly benefit from co-working with a chatbot partner [5].

Grounded on the above-mentioned knowledge in individual differences, we see particular potentials for applying cutting-edge techniques in natural language understanding and sentiment analysis to the design of future agents. Specifically, we advocate for practicing the idea of implicit interaction [7, 8] by incorporating applications of language and emotion intelligence in the design of future agents. Through real-time processing and analyzing verbal and non-verbal cues while interacting with human users, agents should be able to identify individual traits, instead of depending on users' explicit inputs. For instance, it would be rather uneasy if users have to self-report the degree of anxiety in group settings. By contrast, if autonomous agents can better adopt implicit cues to recognize personal characteristics, user experiences can be improved and individual needs can be accommodated more effectively. Recent work has experimented with applying implicatures (i.e., contextual implications beyond the literal meanings of utterances) to design communication agents [12]. In a set of unpublished data, we also found behavioral tendencies, such as whether or not participants commented on a chatbot's performance, can effectively reveal their personality traits (high- or low-anxiety in teams). Overall, we seek more attention to the line of research, in order to create future agents that can offer help to individual teammates more proactively and relevantly.

Proposition 3: Transporting diversity to machine intelligence

Building any artificial intelligence (AI) requires inputs of data, such as ground truth labels that categorize images into cats and dogs. To build smarter agents, there has been an increasing need to assemble knowledge from various fields. As a result, recent literature has posited data as a fundamental design material for AI, and the curation of data can directly impact user experience in human-agent interaction [14]. We see this as a unique opportunity for more diverse opinions and ideas to be heard and adopted. Recently, adopting training data from more diverse sources have gained much attention among machine learning scholars and practitioners, as such an approach not only enhances the robustness of machine learning models but can also reduce the risk of certain human biases being carried over and amplified in AI [13, 6]. In the context of teamwork, we also view this as a means to combat stereotypes. Communication research has long revealed the impact of source agency [4, 19], and even the most brilliant ideas can often be rejected due to the status, associations, and stigma of their owners [15]. To prevent bringing this long-lasting issue to human-agent teams, we consider it particularly critical to "fuel" future teamworking agents with data from a wide variety of sources, and furthermore, to also allow individual team members to constantly contribute materials to enrich the building blocks of their machine partners. Together, we see human-agent interaction as a unique opportunity for ideas to be heard and conversations to be carried on before they are labeled with specific biases.

Proposition 4: Intelligent agents as your ally

Previous research in human-robot interaction has revealed the potentials of including robots as mediators to resolve conflicts in teams [9], while a recent study has also posited that an autonomous agent can serve as "social glue" when human teammates co-work on an AI-mediated platform [18]. Along the same vein, we ask whether autonomous agents can also help to enhance equality and fairness in teamwork. By keeping track of the time and amount of work dedicated by each member, intelligent agents should encourage certain teammates to contribute more while others to ease up. We consider the mediating role of teamworking agents can bring benefits in three-folds. First, we consider such intervention can alleviate the problem of social loafing, by motivating free riders to contribute more to teamwork through directly cuing them up during team conversations, or, for instance, previous research has found computer-mediated platforms that visualized how work was distributed among participants could lead to team responsibility being shared more evenly [10, 21, 11]. Similarly, if an autonomous agent can monitor team dialogues, encouraging outspoken participants to attend to others' opinions while supporting introverted individuals to speak up, we consider this as an opportunity to mitigate group thinks or opinion leadership [15]. On formal occasions, a panel moderator is often relied on to ensure opinions from all members are well expressed, but when individual roles are less clear in certain teamwork scenarios, intelligent agents can potentially chime in. Moreover, whether or not such intervention is successful, team members would blame the bots, instead of directing their dissatisfaction to specific collaborators [9, 18]. Together, we see the above two approaches both can relieve the burdens of individuals who tend to overload themselves in teamwork.

Finally, autonomous agents can also second on marginalized teammates who possess limited support in their work environment, such as women in STEM fields, international students in higher education institutions, or people of color in the creative industry. Previous studies in small group research have found ideas being proposed by these individuals are significantly less likely to be adopted, as there is often a lack of supportive voices to echo on these marginalized members; moreover, the phenomenon is often exacerbated when novel, out-of-the-box ideas are proposed by members of these minority groups [16, 15]. To show support to these marginalized members, future agents need not offer equally innovative inputs, but simply by resonating with their human fellows, these intelligent machines can allow a wider range of opinions and contributions to be taken equally seriously.

Conclusion

To summarize, we consider the design of future agents for human-machine partnerships should take into concern not only group- but also individual-level interests. By setting the stage for individual members to shine, we view this approach can lead to a more inviting and encouraging work environment in the long run, and thus solid team synergy and fruitful performance outcomes. To practice such vision in future human-agent teamwork, we propose four strategies: (1) To place humans at the center of such work relationships, allowing users to define the context, goals, and needs in various collaborative tasks while applying multi-dimensional, user-centric metrics to optimize the algorithmic design for future agents. (2) To practice the concept of implicit design [7] when it comes to accommodating different types of support needed by individual teammates. This can potentially be done through applying the state-of-the-art language and emotion intelligence technology, enabling autonomous agents to proactively sensing and understanding individual traits through verbal and non-verbal cues. (3) To adopt data from more diverse sources when designing and developing intelligent machines, and involve team players to participate and contribute to the building materials of these collaborative agents. (4) To monitor and moderate team conversations and contributions of individual members, ensuring fairness in work distribution, mitigating group thinks, and echoing on marginalized members who experience a lack of support in team settings. All in all, we advocate that future human-machine teamwork should not focus solely on team performance, but greater attention should be drawn to how we can tackle the common challenges in human-human teamwork. Together, we view the partnership with intelligent machines as a precious opportunity for us to re-think and re-engineer collaborative framework —while we leverage the unique talent and capability of each individual teammate, we also lay greater diversity and equality to the ground of our day-to-day team dynamics.

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